Vetting of TESS Transit Signals Using ExoMiner++ and Transfer Learning

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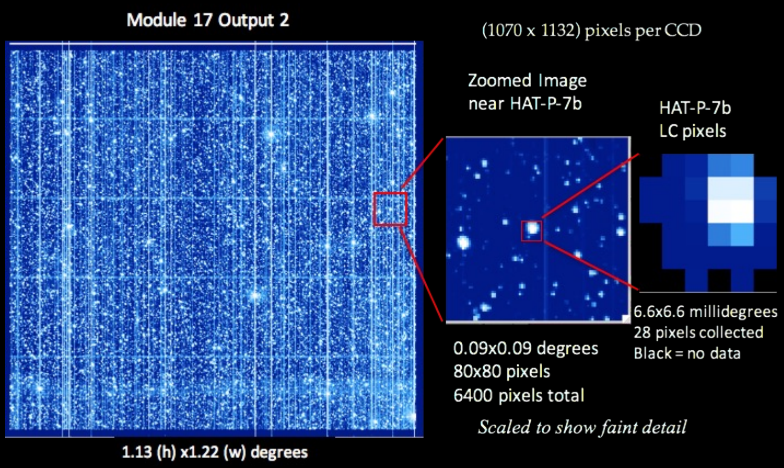
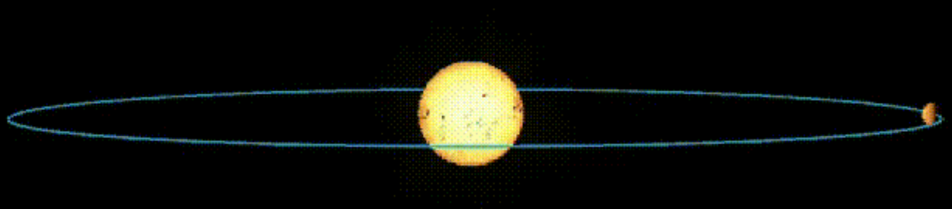
Transit method for planet discovery: Kepler and TESS missions



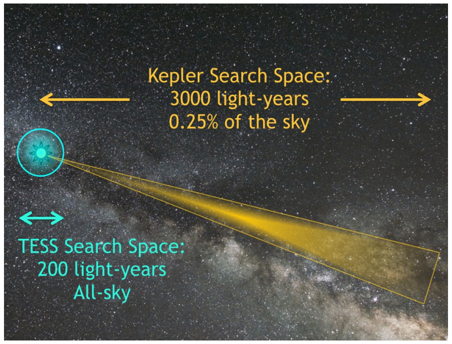


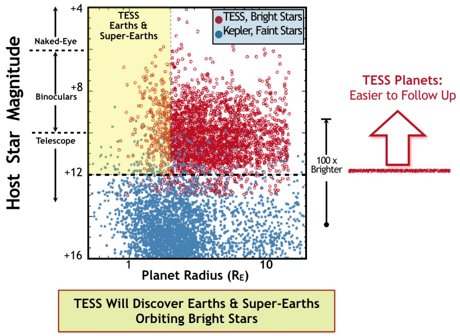
Transiting exoplanets can be detected by taking sequences of low-resolution images of stars (in average, 35 pixels for each star in Kepler telescope)

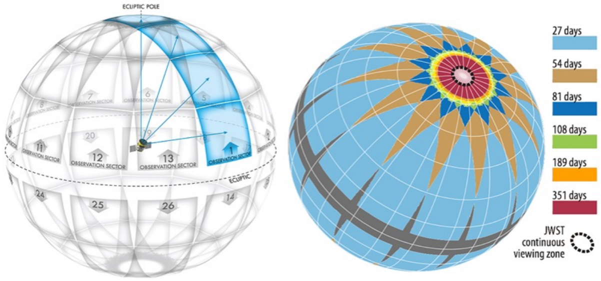
Kepler versus TESS Mission

Difference/Mission	Kepler	TESS
Systematics (Different sources and timescales)	Thermally driven focus changes (long term: 90 days, 372 days), electronic noise in detector readout (short term noise, hours)	Scattered light from Earth & Moon (rapid, minutes to hours), pointing jitter (sub-cadence noise)
Sky Coverage	1/360th of the total sky	Currently > 90% (400X more)
Length of Observations	4 years	28 days in single sector runs
Distribution of the data	Smaller planets, Higher SNR, dimmer distant stars	Larger planets, lower SNR, brighter and smaller (M Dwarfs) nearby stars
Data Annotation	Almost all so far (>2700 planets)	Only a small portion (~200 planets)

Nonetheless, there are so many similarities between the data of two missions. The question is whether we can utilize the data from Kepler to improve the classification performance on TESS

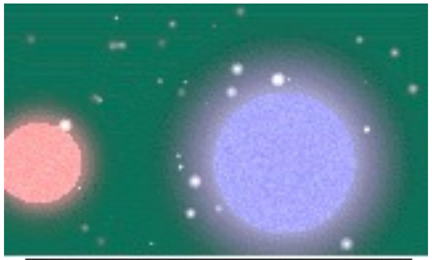


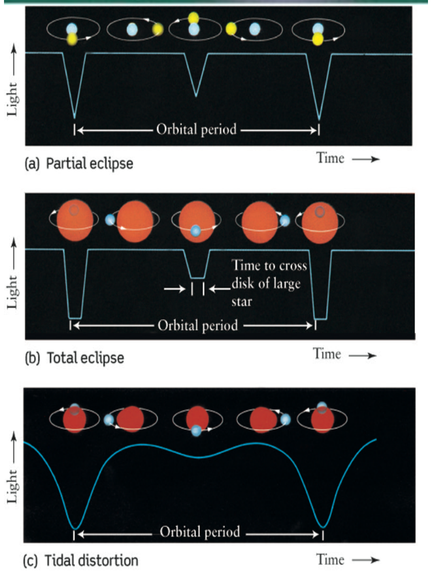




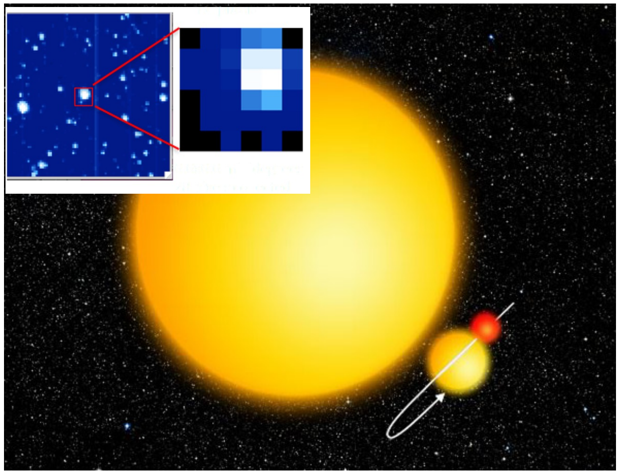
Different sources of false positives

Eclipsing Binaries

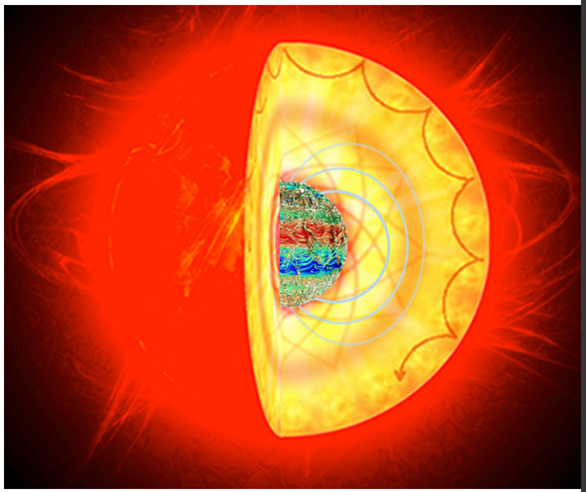




Contamination: background transits

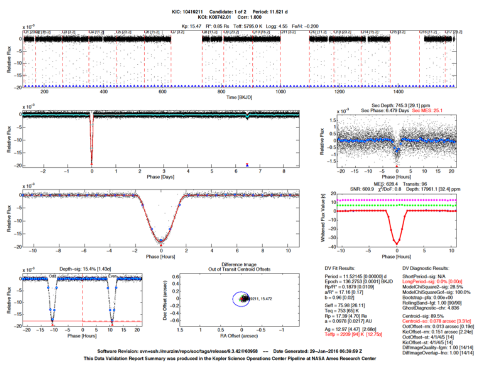


Stellar variations

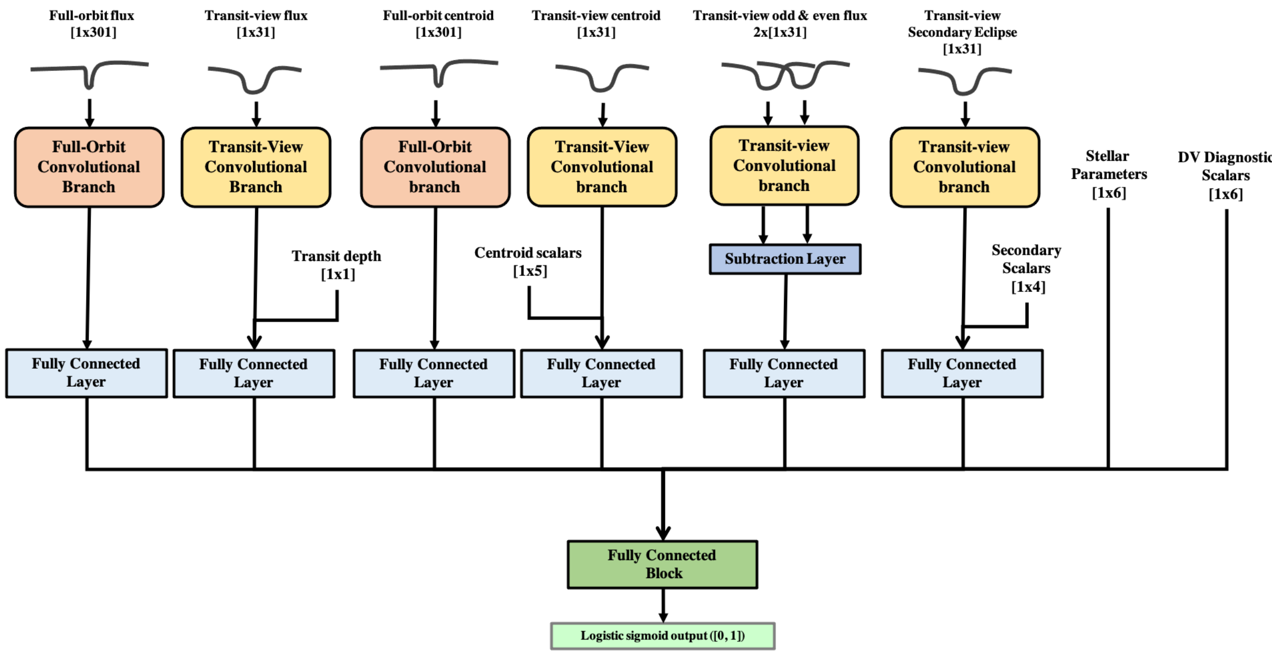


False Positive (FP) Sources → A Classification/Vetting problem

ExoMiner Architecture (Valizadegan et. al. 2022)

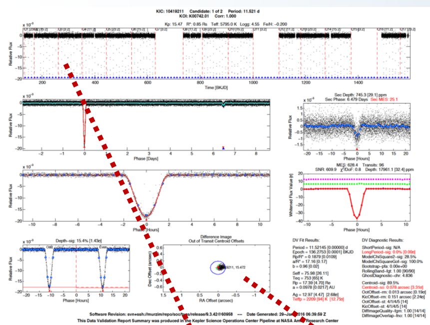


- All unique components of a DV summary report are fed to ExoMiner. Leads to a **highly accurate classifier** ideal for **validating new exoplanets**
- The general architecture inspired by how domain experts vet transit signals. Leads to **better explainability** and **transferability across missions**

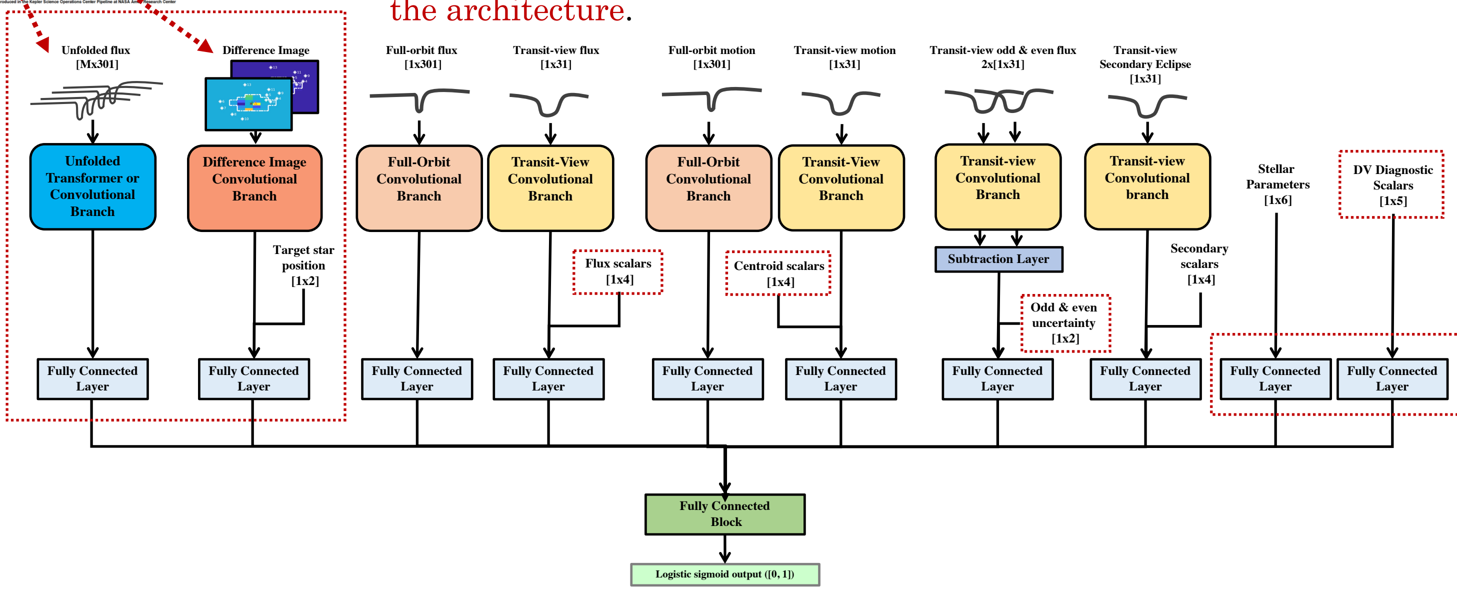


- Each data input requires special preprocessing and handling using a combination of domain knowledge and machine learning

ExoMiner++ Architecture



- Red dotted rectangles highlight the changes from ExoMiner to ExoMiner++
  - **Minor changes**: 1) addition of new scalar values (e.g. target magnitude), 2) removal of some scalar values (e.g. OOT centroid position) to make model suitable for TESS, 3) Correcting some normalizations, 4) minor changes in the architecture.
  - **Major Changes** (work in progress): Addition of two new branches to process unfolded flux and difference images



Building Labeled TESS Data

1. Match SPOC TCEs against ExoFOP TOIs. If a match is found:
   - Use the disposition provided by TFOP WG if it is KP, CP, FP, or FA. PCs and APCs are not used.

2. Match remaining TCEs to EBs from the TSO EB catalog and labeled them as EBs.

3. Match remaining TCEs to TCEs that did not pass the flux triage stage of the Christopher Burke et al's TEC classifier.
   - These TCEs were labeled as non-transiting phenomena (NTP).

4. TCEs that are still without a label are not used.

Results Up to Sector 40

Training Data/Metric	PR AUC[1]	ROC AUC[2,3]	Precision & Recall	Accuracy[3]
Kepler Only (no unfolded Flux)	0.894	0.990	0.867 & 0.810	0.987
TESS Only (no unfolded Flux)	0.913	0.992	0.878 & 0.820	0.988
Kepler+TESS (no unfolded Flux)	0.921	0.995	0.874 & 0.837	0.988
Kepler+TESS (Flux variability only)	0.922	0.994	0.899 & 0.817	0.989
Kepler+TESS (unfolded flux using Transformer)	0.912	0.994	0.868 & 0.849	0.989
Kepler+TESS (unfolded flux using CNN)	0.916	0.995	0.871 & 0.844	0.989

1. PR AUC: Precision Recall Area Under the Curve
2. ROC AUC: Receiver Operating Characteristics Area Under the Curve
3. Accuracy and ROC AUC are not the best metrics because the data are highly imbalanced

Conclusions:

Results Up to Sector 55

Training Data/Metric	PR AUC	ROC AUC	Precision & Recall	Accuracy
Kepler Only (no unfolded Flux)	0.904	0.989	0.870 & 0.831	0.983
TESS Only (no unfolded Flux)	0.940	0.994	0.891 & 0.864	0.986
Kepler+TESS (Flux variability only)	0.942	0.995	0.893 & 0.876	0.987

PR AUC: Precision Recall Area Under the Curve
ROC AUC: Receiver Operating Characteristics Area Under the Curve

Accuracy and ROC AUC are not the best metrics because the data are highly imbalanced

Contributors

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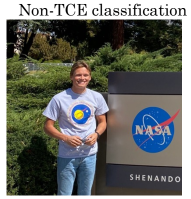

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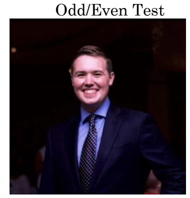

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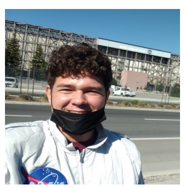

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Questions!

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